1. PROBLEM STATEMENT:

Analysis of stock market for the assessment of the risk has assumed greater significance in India after liberalization and to be very specific over the last decade. Policy makers and investors are well aware of the usefulness of the stock market in mobilizing the resources. Increased participation in the stock market both at, the institutional and individual, domestic and foreign level has brought the Indian Stock Market at new heights. Volatility assumes a greater significance when it comes to investments in stock market. Volatility in stock prices adversely affects the individual earnings and economy's health. It creates the environment of uncertainties and thus hampers the investments.

Investors need to understand that volatility is the inherent feature of stock market. Therefore, if they want to be the part of stock market they should learn how to face this volatility intelligently. Facing the volatility implies efficiently managing the risk of one's investment.

Managing risk is not a onetime process. It requires constant vigilance and efforts on the part of investors. The risk management framework basically involves following steps:

- Define Uncertainty called Volatility.
- Evaluate the potential frequency and severity of losses.
- Develop, select and implement the technique for managing risk.
- Developing suitable strategy for managing risk.
- Monitor the performance and suitability of the risk management methods.

Volatility of stock prices refers to the frequency with which changes in stock prices occurs over a given period of time.

Intelligent investing also implies having the sufficient knowledge of the market as well as the stocks trading in the market. Various categories of stocks from different sectors are listed and traded in the market. Where in the market large cap stocks from different sectors like banking, power, infrastructure, Fast Moving Consumer Goods, Automobile etc. are trading, at the same time there is a market for mid cap and the small cap stocks too from the same sectors. Not all the stocks of all the sectors portray the same behavior in terms of risk and return. Performance of different sector stocks varies and depends on several factors both common and specific to that sector. Therefore, the analysis of volatility for different sectors

acquires greater significance in terms of their sustainability on one side and as well as volatility on the other side.

Value at Risk (VaR) is an important tool which enables the investors to know the potential loss on their investments for a given time period at a certain confidence level. It is popularly used as a tool to manage the risk of investment in individual stocks as well as the portfolio.

Risk management has now become an essential component for all the investors, individual as well as institutional, so that they may withstand sudden ups and downs and fluctuations of the market. The planning should be done in such a way that the investments not only withstands the adverse impacts but could utilize such situations for for value appreciation; this type of strategic planning may be termed as the **risk management with value addition**.

Risk of portfolio can be managed efficiently only when the investors understand the volatility behavior of individual stocks and the interrelationship of the assets constituting the portfolio.

The current research attempts to apply the various steps involved in the risk management framework on the selected sector Indices of National Stock Exchange.

2. VOLATILITY:

As we understand it, volatility implies the ability to change. Volatility refers to the amount of uncertainty or risk about the size of changes in the value of a security or its index value. A higher volatility means that a security's value can potentially vary over a larger range of values. This means that the price of the security can change dramatically. A lower volatility means that a security's value does not fluctuate dramatically, but the changes in its value are at a steady pace over a period of time.

The term 'volatility' is often used in respect of stock market. When the stock market goes up one day, and then goes down for the next five days, then up again, and then down again, that's what we call stock market volatility.

Some people say that volatility is a polite way of referring to investors' nervousness. Investors may think volatility indicates a problem. But many analysts believe that increased volatility can indicate rebound of the market.

Volatility is thus the up-and-down movement of the market. It is usually measured by the standard deviation from the expectation. If we look at the market on a day, when its movement is typically up, much above expectation but not by very much, we say 'market is volatile'. Any movement up or down of the market from its expectation is the volatility.

Historically, the volatility of the stock market is roughly 20% a year and 5.8% a month, but volatility keeps on changing, so we go through periods of high volatility and low volatility.

The biggest driver of volatility is a drop in the market. There are simple leverage reasons why market drops cause volatility. But beyond that simple mechanism, following a drop in the market, volatility typically shoots way up for a time before it dampens down again.

History has witnessed two such sustained drops in the market of United States and Europe in the 2nd quarter of 20th century, first in 1929, and then another at the end of the 1930s. It caused the volatility to run really high, and it continued to be high, even in to World War II until it was clear that the friend countries were going to win the war. After World War II, the volatility dramatically declined and stayed long-term stable for decades. Then pickups in volatility were observed after market drops, like in 1973-1974 and then at the turn of 21st century, the tech bubble collapse and 9/11 led to a burst of volatility, but it dampened down until there was a big increase in volatility, such as with the financial crisis in 1997-1998.

3. VALUE AT RISK (VaR):

"VaR is defined as the maximum potential loss that a portfolio can suffer within a fixed confidence level (*cl*) during a holding period".

Although VaR is useful for financial institutions to see the contours of the risks they face, but the VaR is not sub-additive and does not indicate the size of potential loss, provided the loss exceeds VaR. VaR is also not a coherent risk measure because it does not necessarily satisfy the sub-additivity condition set out by Artzner et al.(1999). Yamai and Yoshiba (2005) observed that VaR is not reliable during market turmoil as it can mislead rational investors. The reason for this failure of VaR is that it is incapable of distinguishing between situations where losses in the tail of dispersion curve are only a bit worse, and those where they are overwhelming. It provides the lowest bound for losses in the tail of the loss distribution and

has a bias towards optimism instead of the conservatism that ought to prevail in risk management.

4. SECTORAL INDICES AT NSE:

The National Stock Exchange (NSE) is the leading stock exchange of India located in Mumbai. It was established in 1992 as the first dematerialized electronic exchange in the country. It has a market capitalization of over a trillion dollars and ranks amongst the top 15 exchanges across the globe. It offers trading across Equities / Bonds and Derivatives. Its equities product offering spans across the following instruments

- Equities
- Indices
- Mutual Funds
- Exchange Traded Funds
- Initial Public Offering
- Security Lending and Borrowing Schemes

Indices allow us to understand market sentiment across a broad spectrum of companies belonging to a particular category. Some of the common categorization of indices are

- Broad Market Indices – Midcap / Smallcap etc.
- Sectoral Indices – Auto / Banking / FMCG / IT / Pharma etc.
- Thematic Indices – Consumption / Service Sector etc.
- Fixed Income Indices – Benchmark GSec / Tenor specific securities etc.

Sector based indices are designed to provide a single value for the aggregate performance of a number of companies representing a group of related industries or within a sector of the economy.

5. REVIEW OF LITERATURE

Studies on Market Risk Estimation:

The birth of market risk estimation methods can be linked to the stock market crash of 1987. It is often referred to as the *Black Monday,* which occurred on October 19, 1987 when stock markets around the world crashed around 20% on a single day. This triggered some

immediate changes across global markets like “circuit breakers” and multiple process overhauls.

This was probably the first event which triggered widespread concerns about existing statistical models and sowed the seeds of present day risk management methods. Due credit must be given J.P. Morgan’s then CEO Mr. Dennis Weatherstone, who asked his division chiefs to answer the question: “How much can we loose on our trading portfolio by tomorrow’s close?”.

In 1992 J.P. Morgan launched RiskMetrics methodology and made their research freely available to everyone. The key motivators to make this information freely available were to promote greater transparency and establish a benchmark for market risk measurement.

Some of the most common risk measures for a portfolio are:

a. Standard Deviation
b. Value at Risk (VaR)
c. Expected Shortfall
d. Marginal VaR

Standard deviation is a poor measure of risk, as it penalizes positive returns as well.

Value at Risk (VaR) can be estimated using the following models:

1. Parametric Models – SMA / EWMA / GARCH
2. Non Parametric Models – Historical Simulation
3. Semi Parametric Models – Extreme Value Theory

The **RiskMetrics (1992)** forecasting methodology, first published by J.P. Morgan (Maomoni, 1994), used exponentially weighted moving averages (EWMA) to forecast volatility and was superior to the Simple Moving Average (SMA) method. EWMA gave more importance to recent data points and their importance decayed over time which helps models react faster to shocks compared to SMA in which a volatile day would assume equal importance till its inclusion in the sample set and would impact the volatility even more when it would drop out.

Angelovska (2013) used SMA/EWMA and back tested forecasted VaR’s using a BLF (Binary Loss Function) error statistics. The obtained equity distribution was fat tailed as

compared to the normal distribution. Also the data was not symmetric, but showed existence of skew, meaning thereby that the returns are asymmetric. Both the models gave acceptable VaR's at the 95% confidence level but broke down at the higher level of 99%. Practitioners prefer simple models like SMA and EWMA. EWMA is able to predict stock market VaR in developed as well as emerging markets.

Many financial institutions even in India are using non parametric approaches, like historical simulations, to estimate VaR.

Goorbergh & Vlaar (1999) performed historical simulation by splitting up a sample into equally long subsamples and construction of VaR for each subsample. It simply takes sample percentiles over a moving sample.

Boudoukh, Richardson & Whitelaw (1998) extended historical simulation by applying exponential weights on them (HS – WHS). Empirical tests showed significant improvements in the precision of VaR forecasts on using the hybrid approach, as compared to RiskMetrics and Historical simulation. The method is especially suited for calculation of VaR of fat tailed and highly skewed data.

Hendricks (1996) applied 12 different VaR models (5 SMA / 3 EWMA / 4 Historical Simulation) over 1000 randomly chosen FX portfolios over a 10 year period and arrived at the conclusion that none of the models was superior on every count. The choice of confidence level (95/99) had a substantial impact on performance of VaR models. Most models were able to predict accurate 95^{th} percentile measures but lost the plot at the 99^{th} percentile.

The ARCH model was invented by **Engle (1982)** during his sabbatical at the London School of Economics in 1979 (The paper was published in 1982). The ARCH (Autoregressive Conditional Heteroscedastic) model describes the future volatility by using historical data. The model proposed assigning weights to past squared forecast errors. Forecasts are first calculated and then the set of weights which make the forecast closest to the variance of the next return are obtained. A maximum likelihood approach is used to estimate these weights. Once the weights are obtained, one can use them for forecasting the future.

In 1986 a student of Engle took the ARCH models further with the development of GARCH by **Bollerslev**. It has become one of the most widely used models in econometric modelling today. It essentially generalizes the purely autoregressive ARCH model to an autoregressive moving average model.

Nelson (1991) introduced EGARCH (Exponential GARCH). It assumed that volatility can respond asymmetrically to past forecast errors and negative returns seemed to be more important predictors of volatility than positive returns.

The widespread success of ARCH/GARCH models can be attributed to them being able to capture unpredictability, fat tails and volatility clustering. Almost every financial asset class exhibits these properties and that has been the key to the success of these models.

Korkmaz & Aydin (2002) analyzed VaR on ISE-30 index, comparing EWMA and GARCH models. While both models were able to satisfactorily estimate VaR at 95 & 99 percentile confidence levels, GARCH provided a more accurate analysis than EWMA.

Ou (2007) did a similar analysis on the Chinese stock markets and concluded that GARCH is superior to the RiskMetrics-EWMA approach at both 95 & 99 percent confidence levels.

Varma (1999) performed such tests on the Indian Stock markets and found that GARCH-GED (Generalized Error Distribution residuals) performs exceedingly well from 90% to 99.75%. The RiskMetrics-EWMA does well at 90% & 95% but breaks down at the 99% and higher confidence levels.

Engel & Gizycki (1999) argued that the cost in terms of forecasting accuracy of using simpler models, like SMA & EWMA, does not appear to be high, as they appear to perform well or often better than complex GARCH models. These findings also find support from the Australian banking industry, where comparatively simpler models of variance/covariance are used in formulating VaR models. The authors do however observe that there is strong evidence to suggest that returns are not normally distributed.

Hull & White (1998) proposed a method for using GARCH / EWMA in conjunction with historical simulation. Their proposed BRW approach involves applying weights that decline exponentially. They tested the approach on 9 years' data for 12 currency pairs and 5 stock indices and provided better than 99 percentile estimates.

Jorion (2000) mentioned that historic models are always one step too late. They start to react after a big move has already occurred. GARCH models will induce a lot of movement in VaR forecasts. Although this may be beneficial in estimating VaR over the next day, the approach may not be well suited to setting risk limits and capital charges. Multivariate GARCH models

are also ill suited to large scale risk management problems, as there are simply too many parameters to estimate.

Dave & Stahl (1998) present a good overview of VaR estimation techniques and infer that historical simulations modulated by a GARCH process are likely to provide better results.

Barone-Adesi, Bourgoin & Giannopoulos (1998) apply the proposed approach with encouraging results on a portfolio replicating a stock market index.

Barone-Adesi, Giannopoulos & Vosper (1999) extend this methodology to a portfolio of derivative securities by using a simulation which is a combination of GARCH modelling (parametric) and historical portfolio returns (non-parametric).

Artzner et al (1999) have identified four essential properties of risks, viz.:

1. Sub additive – The risk of X+Y is never greater than risk of X plus risk of Y;
2. Translation invariance – Cash addition reduces risk of portfolio exactly by the same amount;
3. Positive homogeneity of degree 1 – Doubling of every position doubles the risk; and
4. Monotonicity – If losses in X are greater than risks in Y for all possible scenarios, then risk in X is greater than risk in Y.

Any risk measure which satisfies all these properties was called "Coherent"

Mandlebrot (1963) analyzed returns on cotton prices to argue that portfolio returns demonstrated fat tails. He computed the sample variance of a large number of samples containing the returns of cotton prices and found that the variances did not converge to any limiting value.

Fama (1965) used the DJIA to conclude that stocks are riskier than indicated by deviation of a normal distribution.

Peters (1991) found that the distribution of S&P 500 showed higher peaks, fatter tails and skews. He also estimated the probability of a 3 sigma event under empirical distribution and found it to be twice that of the normal distribution.

VaR failed in the coherent risk measure test prescribed by Artzner et al. (1998), as it was not sub additive, except in the special case when returns would actually be normally distributed. A body of evidences, as shown above, had already piled up, which indicated otherwise.

Einhorn (2008) went to the extent of arguing that VaR is like an air bag that works all the time except when you have an accident.

Bali (2003) studied US treasury yields in order to find a suitable distribution for extreme value and concluded that the extreme value theory provided an accurate method for risk management and a more valid framework for VaR calculation.

Zikovic (2008) highlighted the incoherent nature of VaR. It cannot distinguish between situations where losses are slightly worse than tails and where they are overwhelming. The paper concludes that VaR models fail in accurate estimation of tail losses. ETL models are much better estimators of actual losses. The proposed method is semi parametric and uses volatility transformed tail data.

Corrado & Miller (2005) examined the forecast quality of CBOE VIX based on S&P and Nasdaq stock indices and found that forecast quality of CBOE VIX for S&P has improved significantly in recent years and implied volatilities for Nasdaq provide an even higher quality forecasts of future realized volatility. They found that volatility indexes published by the CBOE easily outperform historical volatility and serve as predictors of future return volatility both for S&P and Nasdaq.

Christensen & Prabhala (1998) found that implied volatility does predict realized volatility in isolation as well as in conjunction with the history of past realized volatility. Their previous work indicated that implied volatility is both biased and inefficient and construed as a vote against the joint hypothesis that option markets' aggregate volatility information is more efficient and the Black-Scholes option pricing formula is valid for S&P Index Options. Their analysis introduced a different research design which used a lower sampling frequency (monthly) to achieve non overlapping periods, which spanned a longer period of time as compared to all the previous studies.

Fleming (1998) examined the performance of S&P Implied volatility as a forecast of future stock market volatility. Results indicated that it is an upward biased forecast but contains relevant information regarding future volatility. He suggested that a linear model which corrects the implied volatilities for upward bias, can provide a useful market based estimator of conditional volatility.

Lamoureux & Lastrapes (1993) examined the behaviour of variances in option markets and their underlying stock indexes. They started with the joint hypothesis that markets are

information ally efficient; option prices are explained by a pricing model and hence forecasts from time series models of stock market should not have predictive content. Their tests suggest that this null hypothesis can be rejected.

Shaikh & Padhi (2015-1) demonstrated seasonal anomalies in the Indian Stock Market. They attempted to find significant day of the week, option expiry and month of the year effects. Their studies reveal a positive significance on Monday and a negative significance on Wednesday. March and December months were found to have significant negative impact on volatility.

Shaikh & Padhi (2015-2) examined the question whether the implied volatility index is 'investor fear gauge' or 'forward-looking expectation' of future market volatility within emerging markets setting –India VIX? They conclude that VIX is the gauge of investor fear, where in the expected stock market volatility rises when the given market declines. It has also been observed that expected volatility being unbiased estimate of the actual return volatility (30-calender days), during the market turmoil VIX is likely to be biased. It has been suggested that the nervousness of investor yields potential profit to the option seller during market crises.

Zheng & Cai (2013) analyzed the implied volatility surface of S&P 500 Index Options. Their base case for testing was based on the constant volatility assumption of the Black Scholes Model. They analyzed index option data from 1996 to 2006 for out of the money options and attempted to fit the data to 3 models of implied volatility. The first one was based on constant volatility black scholes model, the second one had a linear relationship between volatility and moneyness and the third had a quadratic relationship between volatility and moneyness. They found that model 3 had an R square value of 93.4%. They concluded that the assumption of Black Scholes model of constant volatility cannot exist in the real financial markets.

Parasuraman & Ramudu (2011) analyzed the historical volatility of NIFTY Index to empirically prove mean reversion (volatility cone effect). The average, maximum and minimum observed volatilities tend to converge when the rolling period increases. They find that implied volatility is different across various time periods in the horizon and for various exercise prices. The average implied volatilities of calls and puts on NIFTY also showed differences.

Kumar (2008) analyzed the information content of implied volatility estimators and the historical volatility in forecasting future realized volatility using NIFTY Options. Implied volatility was estimated using Black Scholes model and its relationship with future volatility was examined. It was observed that the Implied volatility estimators have information about future volatility and hence they dominate historical volatility estimators. Implied volatility using call options fared much better than those from put options. The results indicated that implied volatility is a rational forecast of future realized volatility.

Goudarzi & Ramanarayanan (2011) studied the effect of good and bad news on volatility in the Indian stock markets using asymmetric ARCH models during the global financial crisis of 2008-2009. They used 10 years data of the BSE500 Index. They concluded that bad news in the Indian Stock markets increases volatility more than good news.

Kaur (2004) investigated the nature and characteristic of stock market volatility in India. The paper concluded that return and volatility on various weekdays have somewhat changed after introduction of rolling settlements in December 1999. There is mixed evidence of return and volatility spill over between the US & Indian stock markets.

Neely (2005) used implied volatility of three month euro dollar interest rates from 1985 to 2001 and evaluated its ability to predict realized volatility. Implied volatility showed that uncertainty about short term interest rates has been falling for almost 20 years due to fall in level of interest rates and inflation. Changes in implied volatility are usually coincident with major news about stock markets, economy and/or monetary policy.

Rakesh (2014) studied volatility of CNX FMCG and CNX Auto Indices and compared them with the CNX NIFTY Index. He analyzed relevant data from January 2012 to June 2014 and examined the relationship across the sector in terms of risk and influence of risk on time intervals. He found that there was a difference in the mean values of these sectoral indices.

Nagendra, Haritha & Ravi (2014) analyzed the correlation between NSE NIFTY and sectoral indices using data from 2006 to 2010. They found that all seven Indices of NIFTY have a correlation of more than 0.60 with the NIFTY index. They concluded that NIFTY has an influence on the performance of the sectoral indices and FMCG and Pharma indexes are less influenced by other sectoral indices.

Guha, Dutta & Bandopadhyay (2016) discussed risk in terms of beta of all sectoral indices of NSE with respect to NIFTY and their performance in terms return per unit risk. They

found that FMCG is the most defensive sector followed by Pharma and Auto. Realty exhibited the highest beta of 2.2 followed by metal and IT. NIFTY returns can be explained to a tune of 95% from six sectoral indices (Auto, Energy, Metal, Pharma, FMCG, PSU Banks) out of the total eleven.

Shanmugasundram & Benedict (2013) studied sectoral NIFTY Indices from 2004 to 2012 to analyze the risk factor differences across the risk of sectoral indices and NIFTY Index. Their results showed that there is no difference in the standard deviation among various sectoral indices. The results show significant differences in the mean scores of various time intervals.

Sridhar & Pandian (2012) studied the return and risk element of investing in shares of NSE Junior Nifty companies. Data was collected over a 5 year period from 2005 to 2009. The volatility was analyzed using extreme value estimators. The study revealed that the risks associated with banking industry stocks is high whereas it is moderate in pharma and IT stocks.

Dutta & Bhattacharya (2008) estimated VaR of S&P CNX Nifty Index using Historical Simulation VaR and Bootstrapped VaR and analyzed their relative performances. The main purpose of using bootstrapped historical VaR was that it takes care of the necessity of large data for model validation even when the sample size is not adequate. They found that in non linear data sets which may not have all stressed scenarios, the use of bootstrapped historical VaR method is a better choice.

Engle (2001) provides a good introduction to ARCH/GARCH models, which have been fairly successful in application to finance. They present an example of risk measurement that could be the input to a variety of economic decisions. The analysis of ARCH/GARCH models and their extensions provides a statistical stage on which many theories of asset pricing and portfolio analysis can be exhibited and tested.

Goyal (2000) analyzed the performance of various GARCH models in terms of their ability of delivering volatility forecasts for stock return data. Volatility forecasts obtained from a variety of mean and variance specifications in GARCH models were compared to a proxy of actual volatility calculated by using daily data. In-sample tests suggest that a regression of volatility estimates on actual volatility produces R square of less than 8%. Out-of-sample tests indicated that a simpler ARMA specification performs better than a GARCH-M model.

Ou & Wang (2011) proposed non linear volatility models based on Gaussian processes combined with GARCH and EGARCH models. The empirical analysis of simulated data showed that these hybrid models can capture well the symmetric and asymmetric effects of news in volatility and generate superior performance of volatility prediction than the corresponding classic models.

Dowling & Muthuswamy (2005) created a VIX based on index options dubbed AVIX. They found that AVIX exhibits large negative first order autocorrelation and is also negatively correlated with lagged and contemporaneous index returns. As a predictor of future volatility AVIX performs poorly compared to historical volatility. When non synchronous trading is controlled, AVIX exhibits a much stronger relationship with future volatility.

Frijns, Tallau & Tourani-Rad (2010) constructed a volatility index (AVX) for the Australian share market. They showed that the AVX is a superior forecaster of future stock market volatility. It has the highest forecasting power relative to alternate forecast methods, like RiskMetrics and GARCH. The AVX provides important information regarding the stock market returns.

Radha & Thenmozhi (2006) forecasted short term interest rates (91 day T Bill/MIBOR/Call Money) using univariate models, like ARIMA, ARMA-GARCH and ARMA-EGARCH models, using 6 year data from 1999 onwards. Their results show that the interest rate time series have volatility clustering effect and hence GARCH based models are more appropriate for forecasting than the other models. They found that for commercial paper rates, ARIMA-EGARCH was the most appropriate model, while for the other rates, ARIMA-GARCH was the most appropriate model for forecasting.

Hansen & Lunde (2005) compared around 330 ARCH type models in terms of their ability to determine conditional variance. The models were compared for their forecasting power on DM-$ exchange rate and IBM return data. Though they could not find any evidence that GARCH(1,1) is outperformed by the more sophisticated models in their analysis of exchange rates, however, GARCH(1,1) is clearly inferior to the models that can accommodate a leverage effect.

Venkatraman & Sowmya (2014) studied stock market volatility by analyzing 4 stocks (ITC, Infosys, SBI and Reliance Industries Limited) and NIFTY. They found that dispersion and volatility in NIFTY was the highest and was much lower in the individual stocks. On an

intraday basis all the 5 benchmarks analyzed showed volatility clustering with some months having extreme volatility and some months having very low volatility.

Sehgal & Vijaykumar (2008) studied the relationship between implied volatility and moneyness, referred to as volatility smile. They used daily data for S&P NIFTY Index, Call and Put Options and the underlying market index for the period from 2004 to 2005. They found that the volatility function exhibits a positive slope in the Indian context. They also showed that historical volatility and time to expiration are the potential determinants of smile asymmetry in India.

Banerjee & Kumar (2011) compared the performance of GARCH and VIX in predicating the underlying volatility of S&P CNX NIFTY Index. They found that the forecast error is minimum for VIX. This indicates that a model free estimator of volatility captures underlying volatility better than an econometric model of volatility (GARCH). This has significant impact for a volatility trader, who can observe the VIX and have a view of the volatility of the underlying cash market.

Swarna Lakshmi (2013) used ARCH model to measure the volatility in NIFTY and various sectoral indices in India over a period starting from 2008 to 2013, keeping in view the high volatility taking place in Indian market, following the meltdown all over the world around the year 2007. The study included 11 sectoral indices of NSE, viz., NSE CNX Auto, NSE CNX Bank, NSE CNX Energy, NSE CNX Finance, NSE CNX FMCG, NSE CNX IT, NSE CNX Media, NSE CNX Metal, NSE CNX Pharma, NSE CNX PSU Bank and NSE CNX Realty. It was observed that Realty sector witnessed higher volatility as compared to any other sectot. Attempt has been made to find out reasons for the same.

Pafka & Kondor (2001) analyzed the performance of RiskMetrics and observed that in spite of the fact that the RiskMetrics model completely ignores the presence of fat tails in the distribution function, it performs satisfactorily well. They further observed that the success of RiskMetrics is the artefact of the choice of the risk measure. First, the outstanding performance of volatility estimates is basically due to the choice of a very short (one-period ahead) forecasting horizon. Second, the satisfactory performance in obtaining Value-at-Risk by simply multiplying volatility with a constant factor is mainly due to the choice of the particular significance level.

Dixit, Roy & Uppal (2013) applied 'Artificial Neural Network' for predicting India Volatility Index. Artificial neural network (ANN) modelling technique was employed to forecast the upwards or downwards movement in next trading day's volatility using India VIX (a volatility index based on NIFTY Index Option prices) based indicators. The study reveals that ANN models are handy in forecasting the downwards movement in VIX. The knowledge of more probable downwards movement in volatility might be of significant value to the investors and help them in making decisions related to trading.

Summary of Research Papers Reviewed

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
1	Angelovska (2013-2)	Managing market risk with VaR (Value at Risk)	SMA/EWMA	Acceptable VaR at the 95% confidence interval but breaks down at the higher level of 99%.
2	Goorbergh and Vlaar (1999)	Value-at-risk analysis of stock returns	Historical simulation (HS)	Changing volatility over time is the most important characteristic of stock returns when modelling value-at-risk; For high confidence levels, the fat tails of the distribution can best be modelled by means of the t-distribution; on the other hand the performance of tail index estimators is found to be much worse.
3	Boudoukh, Richardson and	Hybrid Approach to Calculate Value at Risk	Extension of HS by	Significant improvements in the

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
	Whitelaw (1998)		applying exponential weights on them (HS–WHS)	precision of VaR forecasts obtained on using the hybrid approach
4	Hendricks (1996)	Evaluation of Value-at-Risk Models Using Historical Data	SMA/EWMA/ HS	The choice of confidence level (95/99) exhibits substantial impact on the performance of VaR models.
5	Engle (1982)	Autoregressive Conditional Heteroscedasticity with Estimates of the Variance	ARCH	Future volatility can be predicted by using historical data.
6	Bollerslev (1986)	Generalized Autoregressive conditional heteroskedasticity	GARCH	Generalizes the purely autoregressive ARCH model to an autoregressive moving average model.
7	Nelson (1991)	Conditional Heteroskedasticity in Asset Returns	EGARCH	Volatility can respond asymmetrically to past forecast errors and negative returns seemed to be more important predictors of volatility than positive returns.
8	Korkmaz & Aydin (2002)	EVMA and GARCH Methods in VaR	EWMA & GARCH	While both the models were able to

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
		Calculations: Application on ISE-30 index		satisfactorily estimate VaR at 95 & 99 percentile confidence levels, GARCH provided a more accurate analysis than EWMA
9	Ou (2007)	Evaluating predictive performance of value-at-risk models in Chinese stock markets	EWMA & GARCH	GARCH is superior to the EWMA approach at both 95 & 99 percent confidence levels.
10	Varma (1999)	Value at Risk Models in the Indian Stock Market	GARCH-GED	GARCH-GED (Generalized Error Distribution residuals) performs exceedingly well from 90% to 99.75%. The EWMA does well at 90% & 95% but breaks down at the 99% and higher confidence levels
11	Engel and Gizycki (1999)	Conservatism, accuracy and efficiency: comparing Value-at-risk models.	SMA /EWMA/ GARCH	GARCH is costlier than EWMA/SMA and the returns are not normally distributed.
12	Hull and White (1998)	Incorporating volatility for updating the historical simulation method for “value-at-risk."	GARCH/ EWMA/HS	When three approaches are applied together, they produce better than 99 percentile estimates.

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
13	Dave and Stahl (1998)	Accuracy of VaR estimates based on the variance-covariance approach.	GARCH	Historical simulations modulated by a GARCH process is likely to provide better results.
14	Barone-Adesi, Bourgoin and Giannopoulos (1998)	Market Risk	HS VaR	Proposed methodology leads to a faster evaluation of VaR. This is because the process requires a simple historical simulation to be run through a preset time series filter.
15	Barone-Adesi, Giannopoulos and Vosper (1999)	VaR without correlations for portfolios of derivative securities.	GARCH+ Historical Simulation	The model handles worst case scenarios for large portfolios. It takes into account current market conditions and does not rely on the knowledge of the correlation matrix of security returns.
16	Artzner et al. (1999)	Coherent Measures of Risk	Sub additive/ Translation invariance/ Positive homogeneity of degree 1/ Môn tonicity	Any risk measure which satisfies all these properties was called "Coherent"
17	Mandlebrot	The variation of certain	Analyzed	Variances did not

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
	(1963)	speculative prices	returns on cotton prices to establish that portfolio returns demonstrate fat tails	converge to any limiting value.
18	Fama (1965)	The behaviour of stock-market prices	DJIA Index VaR	Stocks are riskier than indicated by deviation of a normal distribution.
19	Peters (1991)	A chaotic attractor for the S&P 500	S&P 500 Index VaR	Distribution of S&P 500 showed higher peaks, fatter tails and skews.
20	Einhorn (2008)	Private Profits and Socialized Risk	VaR analysis	VaR is like an air bag that works all the time except when the portfolio suffers an accident.
21	Bali (2003)	An Extreme Value Approach for estimating volatility and Value at Risk	Studied US treasury yields in order to find a suitable distribution for extreme value	The extreme value theory provided an accurate method for risk management and a more valid framework for VaR calculation.
22	Zikovic (2008)	A story of Value at Risk and Expected Tail Loss	Studied incoherent nature of VaR	It cannot distinguish between situations where losses are slightly worse than tails and where they are

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
				overwhelming. ETL models are much better estimators of actual losses.
23	Corrado and Miller. (2004)	The forecast quality of CBOE implied volatility indexes	OLS Volatility forecast regression	Volatility indexes published by the CBOE easily outperform historical volatility, as predictors of future return volatility both for S&P and Nasdaq.
24	Christensen and Prabhala (1998)	The relationship between implied and realized volatilities	OLS estimation	Implied volatility does predict realized volatility in isolation as well as in conjunction with the history of past realized volatility.
25	Fleming (1998)	The quality of market volatility forecasts implied by S&P 100 index option prices	Generalized Methods of Moments	Results indicated that implied volatility has an upward biased forecast but contains relevant information regarding future volatility.
26	Lamoureux and Lastrapes (1993)	Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities	OLS and GARCH models	Historical variance has explanatory capabilities for future volatility and implied volatility based predictors are not superior.

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
27	Shaikh and Padhi (2015-1)	The behaviour of option's implied volatility index : A case of India VIX	OLS and GARCH estimation	There is a strong presence of seasonal anomalies in the Indian Stock market. It exhibits day / expiry / month effects.
28	Zheng and Cai (2013)	Modelling the Implied Volatility Surface-: A study of S&P 500 Index options	Regression models	The assumption of Black Scholes model of constant volatility cannot exist in the real financial markets.
29	Parasuraman and Ramudu (2011)	Historical and Implied Volatility: An investigation into NSE NIFTY Futures and Options	Averages and GARCH(1,1)	The average, maximum and minimum observed volatilities tend to converge when the rolling period increases. They find that implied volatility is different across various time periods on the horizon and for various exercise prices. The average implied volatilities of calls and puts on NIFTY also showed differences.
30	Kumar (2008)	Information Content of Option Implied Volatility: Evidence from the Indian Market	Regression, RMSE	Implied volatility estimators provide information about future volatility and dominate

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
				historical volatility estimators.
31	Goudarzi and Ramanarayanan (2011)	Modelling asymmetric volatility in the Indian stock market	EGARCH & TGARCH	In the Indian Stock market a bad news increases volatility more than a good news
32	Kaur (2004)	Time varying volatility in the Indian stock market	GARCH	There is mixed evidence of return and volatility spillover between the US & Indian stock markets
33	Neely (2005)	Using implied volatility to measure uncertainty about interest rates	Regression Analysis	Changes in implied volatility are usually coincident with major news about stock markets, economy and/or monetary policy
34	Rakesh (2014)	A Study on Volatility of FMCG and Auto Indices of National Stock Exchange	Hypothesis Testing, T test	There was a difference in the mean values of these sectoral indices
35	Nagendra, Haritha, and Ravi (2014)	NSE NIFTY and its correlation with sectoral indexes.	Correlation analysis	NIFTY has an influence on the performance of the sectoral indices and FMCG and Pharma indexes are less influenced by other sectoral indices.
36	Guha, Dutta, and	Measurement of Risk V/S	Regression,	FMCG is the most

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
	Bandyopadhyay (2016)	Return of Indian Sectoral Indices	Beta analysis, Standard deviations	defensive sector followed by Pharma and Auto. Realty exhibited the highest beta of 2.2 followed by metal and IT. NIFTY returns can be explained to a tune of 95% from six (Auto, Energy, Metal, Pharma, FMCG, PSU Banks) out of the total eleven sectoral indices.
37	Shanmugasundram and Benedict (2013)	Volatility of the Indian sectoral indices-A study with reference to national stock exchange	ANOVA, T Test	Their results showed that there is no difference in the standard deviation among various sectoral indices. The results show significant differences in the mean scores of various time intervals
38	Sridhar and Pandian (2012)	Return and Volatilty Analysis of National Stock Exchange (NSE) NIFTY- Junior Companies	Garman Klass, Parkinson Estimator	The study revealed that the risks associated with banking industry stocks are high, whereas the risk is moderate in pharma and IT stocks
39	Dutta and	A Bootstrapped Historical	Historical	They found that in non

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
	Bhattacharya (2008)	Simulation Value at Risk Approach to S & P CNX Nifty	bootstrapped VaR	linear data sets which may not have all stressed scenarios, the use of bootstrapped historical VaR method is a better choice.
40	Engle (2001)	GARCH 101: The use of ARCH/GARCH models in applied econometrics.	ARCH/GARCH	The analysis of ARCH/GARCH models and their extensions provides a statistical stage on which many theories of asset pricing and portfolio analysis can be exhibited and tested.
41	Goyal (2000)	Predictability of stock return volatility from GARCH models.	ARMA/GARCH	Out-of-sample tests indicated that a simpler ARMA specification performs better than a GARCH-M model.
42	Ou and Wang (2011)	Modeling and forecasting stock market volatility by gaussian processes based on GARCH, EGARCH and GIR models	GARCH	The empirical analysis of simulated data showed that these hybrid models can capture well the symmetric and asymmetric effects of news in volatility and generate superior

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
				performance of volatility prediction than the corresponding classic models.
43	Dowling and Muthuswamy (2005)	The implied volatility of Australian index options	VIX	As a predictor of future volatility AVIX performs poorly as compared to historical volatility. When non-synchronous trading is controlled, AVIX exhibits a much stronger relationship with future volatility.
44	Frijns, Tallau, and Tourani-Rad (2010)	Australian implied volatility index	VIX, RiskMetrics, GARCH	VIX has the highest forecasting power relative to alternate forecast methods, like RiskMetrics and GARCH
45	Radha and Thenmozhi (2006)	Forecasting short term interest rates using ARMA, ARMA-GARCH and ARMA-EGARCH models	ARMA, GARCH, EGARCH	Interest rate time series have volatility clustering effect and hence GARCH based models are more appropriate for forecasting as compared to other models
46	Hansen and Lunde (2005)	A forecast comparison of volatility models: Does	ARCH type models	They found no evidence that GARCH(1,1) is

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
		anything beat a GARCH (1, 1)?		outperformed by more sophisticated models in the analysis of exchange rates. However, it was observed that GARCH(1,1) is clearly inferior to the models that can accommodate a leverage effect
47	Venkatraman and Sowmya (2004)	A Study on Future Stock Market Volatility, with special reference to Nifty Index	Logarithmic returns, Parkinson model and Garman & Klass models	They found that the dispersion and volatility in NIFTY show the highest values, whereas they are much lower in the individual stocks.
48	Sehgal and Vijayakumar (2008)	Determinants of implied volatility function on the NIFTY index options market: Evidence from India	OLS, Causality Testing	They find that the volatility function exhibits a positive slope in the Indian context. They also show that historical volatility and time of expiration are the potential determinants of smile asymmetry in India
49	Banerjee and Kumar (2011)	Realized volatility and India VIX	VIX, GARCH	They find that the forecast error is minimum for VIX. This indicates that a model

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
				free estimator of volatility captures underlying volatility better than an econometric model of volatility (viz., GARCH).
50	Swarna Lakshmi (2013)	Volatility Patterns in various sectoral indices in Indian Stock Market	ARCH model	ARCH model is used to measure the volatility in NIFTY and 11 sectoral indices in India. It was observed that realty sector shows higher volatility than any other sector.
51	Shaikh & Padhi (2015-2)	The implied volatility index: Is 'investor fear gauge' or 'forward-looking'?	Empirical models	It has been concluded that India VIX is both; it is the fear indicator of the investor's nervousness, and the best unbiased estimate of future stock market volatility.
52	Pafka & Kondor (2001)	Evaluating the RiskMetrics methodology in measuring volatility and Value-at-Risk in Financial Markets	RiskMetrics model	Based on the assumption of normally distributed returns, the RiskMetrics model completely ignores the presence of fat tails in

SL. No.	Study Reference	Study objective/ study description	Methodology used	Findings
				the distribution function. Nevertheless, RiskMetrics performs satisfactorily well. The success of RiskMetrics depends on the choice of risk measure, i.e., forecasting horizon and significance level.
53	Dixit, Roy & Uppal (2013)	Predicting Indian Volatility Index: Application of Artificial Neural Network for predicting India Volatility Index	Neural Network	Artificial neural network modelling technique has been successfully used to forecast the upwards or downwards movement in next trading day's volatility using indicators based on India VIX. The study reveals that ANN models are more efficient in forecasting the downwards movement in VIX.

BOOKS REVIEWED

Book Review #1

Morgan, J.P. & Reuters (1996), " RiskMetrics™ technical document" (4th Edition), Morgan Guaranty Trust Company, Newyork

This is the reference book/document for RiskMetrics. It covers all aspects of RiskMetrics It is meant to serve as a reference to the methodology of statistical estimation of market risk. This book/ document reviews 1. The conceptual framework underlying the methodologies for estimating market risks. 2. The statistics of financial market returns. 3. How to model financial instrument exposures to a variety of market risk factors. 4. The data sets of statistical measures. Dozens of professionals at J.P. Morgan have contributed to the development of this market risk management technology. RiskMetrics is a set of tools that enable participants in the financial markets to estimate their exposure to market risk under what has been called the "Value-at-Risk framework". RiskMetrics has three basic components:

- A set of market risk measurement methodologies outlined in this document;
- Data sets of volatility and correlation data used in the computation of market risk; and
- Software systems developed by J.P. Morgan, subsidiaries of Reuters, and third party vendors that implement the methodologies described herein.

With the help of this document and the associated line of products, users should be in a position to estimate market risks in portfolios of foreign exchange, fixed income, equity and commodity products.

The RiskMetrics (1992) forecasting methodology uses exponentially weighted moving averages (EWMA) to forecast volatility and has been found to be superior to the Simple Moving Average (SMA) method. EWMA gives more importance to recent data points and their importance decays over time, which helps models react faster to shocks as compared to SMA, in which a volatile day would assume equal importance till its inclusion in the sample set and would impact the volatility even more when it would drop out from the sample.

Book Review #2

Jorion, Philippe (2006), "Value at Risk: The New benchmark for managing financial risk" , (3rd edition), The McGraw-Hill Companies INC., U.S.A.

Even as risk management assumes an increasingly central role in financial institutions, the actual understanding of financial risk continues to be problematic. Financial disasters still occur—witnesses are: Asia's 1997 market turmoil, Russia's 1998 default, and the near-collapse of Long Term Capital Management, as institutions either fail to see or, in some cases, completely ignore easily recognizable hallmarks of impending financial disaster. For financial risk managers attempting to navigate this tumultuous or rapidly changing environment, the updated, expanded, and substantially revised 3rd edition of "Value at Risk", will provide the latest advances in risk management.

This book mentions that historic models are always one step too late. They start to react after a big move has already occurred. GARCH models induce a lot of movement in VaR forecasts. Although this may be beneficial in estimating VaR over the next day, the approach may not be well suited for setting risk limits and capital charges. Multivariate GARCH models are also ill suited to large scale risk management problems, as there are simply too many parameters to estimate.

5. RESEARCH GAPS OBSEREVED

A lot of research papers have evaluated various models for their performance in estimation of VaR and predicting volatility for different types of portfolios, but none of them has been found to be superior on every count. Most of the models though fair well at 95%, they fail at 99% confidence level. While there is extensive research available on Value at Risk (VaR) estimation and performance of various models on financial assets of developed economies, the amount of research published on emerging markets is far lower. Also, the available research on emerging markets is not only limited to major stock indexes, the cross section of data used is also quite narrow. Most of the models focus on the data which is easily available, like currencies and/or equity indices. Research papers investigating Indian markets are even lower in number. Also, the focus of the present research has been mainly on the indexes and only very little efforts have been made to investigate sectoral indices. VIX construction is an area, where some recent work has been done to create proxy indices even for developing economies. Studying their behaviour can add a different dimension to the existing field of research, which concentrates more on indices.

6. MOTIVATION:

These days, study of volatility and risk management are essential components of any Business Organization or a Financial Institution. Forecasting volatility of market has become even more important in the wake of global crash down of the market recently witnessed in 2007-2008. The volatility forecast provides an opportunity to the investor to plan his/her portfolio and assets in such a manner to take advantage of the falling market and convert it in to profit or suffer minimum loss in extreme conditions. Several models exist for prediction of volatility and calculation of Value-at-Risk. It will be interesting to investigate relative performance of different models and their limitations. Which model performs better for a particular commodity and the factors influencing its performance? Search for a universal model applicable to all types of commodities is even more important. Further modification of a model for realistic prediction of volatility and VaR in context of global markets is a challenging problem.

Since Indian economy is rapidly growing and it has now acquired an important place in global economy and since enough research has not been done so far on Indian markets, it made me take up research on Indian markets, so that the outcome of the proposed research may be helpful to Indian investors and Indian Business/Financial Organizations to make better risk management and suffer no losses or minimum losses in a rapidly falling brisk or violent market.

7. RESEARCH FRAMEWORK:

The selection of an appropriate Value-at-Risk methodology is a challenge both for the researchers as well as practitioners. The challenges take formidable shapes due to non-linearity of the data set and also non-availability of larger data set. The Historical Simulation Value-at-Risk can take care of the non-linearity of the data set, as it does not take any distribution assumption, like Variance-Covariance method where underlying assumption is that the data set follows a linear distribution. But conventional Historical Simulation methods require at least 3 to 5 years' data or even more. The Bootstrapped Historical Simulation takes care of the non-availability of large data set, by bootstrapping, while retaining the main characteristics of the true distribution. Some of the important methods used for market risk estimation, are:

I) Standard deviation;

II) Equally weighted moving average or Simple moving average;

III) Exponentially weighted moving average;

IV) Historical simulation method;

V) ARCH (Autoregressive Conditional Heteroscedastic) model;

VI) GARCH (Generalized Autoregressive Conditional Heteroscedastic) model; and

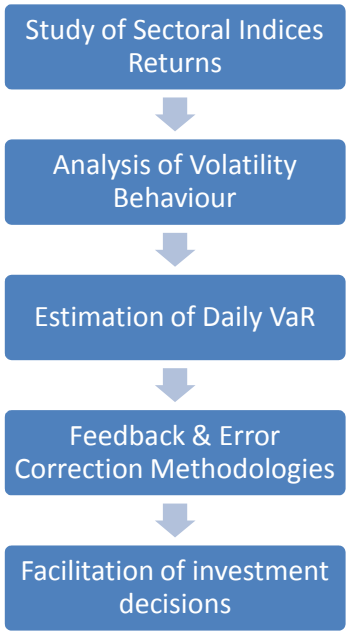
VII) Model based on Artificial Neural Network.

In the proposed research, relative performance of the above mentioned models (at least 3 models) is to be examined in context of Indian markets. Relevant methodology will be developed to apply the models for prediction of volatility and calculation of VaR by using data from 2006 to 2015 and thereafter, so as to include the period of global turbulence occurring in 2007 and the turmoil in Indian market occurring in 2008.

The performance of a model can be measured by examining the distribution of the standardised residuals. The statistical parameters of the distribution of the standardised residuals can be compared with those of the normal distribution. The important statistical parameters of distribution are : i) Mean; ii) Median; iii) Standard Deviation; iv) Quartile Deviation; v) Skewness; vi) Excess Kurtosis, vii) Maximum: vii) Minimum etc.

As most of the portfolio managers in India benchmark their portfolios with a reference index, like S & P CNX Nifty, it is proposed to take S & P CNX Nifty as the data set, which is easily available from the website of NIFTY. NIFTY provides indexes, like opening, close, low and high of asset value on daily basis for the working days. In the proposed research, indexes for about fifteen important commodities covering at least three sectors and currency rates, like value of rupee in terms of US $ and Euro may be taken for calculation of VaR and prediction of volatility. It is proposed to apply different models and techniques (as mentioned above), for calculation of VaR and prediction of volatility from the sectoral indices taken from NIFTY. The study focuses largely on the relative performance of different models for different types of sectoral indices/ commodities and locate the parameters which influence the accuracy of results. Attempt may be made to identify if it already exists, else design a universal model, which could be applied to different types of commodities for prediction of VaR and market volatility with desired efficiency and accuracy in each case, in context of the Indian market.

The research framework will be divided into the following segments


Study of Sectoral Indices Returns
Analysis of Volatility Behaviour
Estimation of Daily VaR
Feedback & Error Correction Methodologies
Facilitation of investment decisions

In the light of the above, following objectives of research may be set:

8. OBJECTIVES AND RESEARCH QUESTIONS:

The proposed study has the following objectives:

a) To test the volatility in the sectoral indices.
b) To test the volatility in the derivatives market.
c) To Estimate the Value at Risk on the basis of volatility.

Problem Questions:

i. Do the volatility of sector indices increases with time?
ii. What is the volatility behavior in the upside and downside market conditions?
iii. What is the relationship between the systematic risk and the residual risk of sector indices?
iv. Does the VaR estimates calculated from Conditional Volatility estimates reliable?

9. SCOPE OF THE STUDY:

Risk management techniques applied in the proposed research may be used to assess the risk return characteristics in the other investment options as commodities, real estate; Debt market etc. Thus, the scope of the study envelopes the whole ambit of the wealth management

10. ***RESEARCH METHODOLOGY****:*

10.1 Universe of the study

Bombay Stock exchange and National Stock Exchange are two widely accepted and popular stock exchanges in India, which are treated as barometer of Indian economy. Universe for the study is all the sectoral indices on Bombay Stock Exchange (BSE) and National Stock Exchange (NSE).

10.2 Sample

India adopted the policy of Liberalization in the year 1991.The stock market was not stable during the initial years of financial sector reforms. The market experienced both constructive and appalling moves. Any kind of research statistics applied on the period of structural changes might give the biased results. It was only after 7-8 years of reforms that market took an appropriate silhouette. Hence, the period of study under the proposed research has been taken from the year 2000 to year 2017.

Sample of the study includes all the sector indices, which have been consistently listed and being traded on NSE separately, since year 2000. We will be focusing on the Banking / Information Technology / Infrastructure / Midcap sectors for our study.

10.3 Data Collection:

Source of data collection is secondary. Data for the purpose of the proposed research will be collected from the website of NSE and Prowess data base of CMIE.

10.4 Tools for data Analysis:

Following tools will be applied for analysis of data:

10.4.1 To calculate the overall Risk/ Volatility of Sector Portfolio:

The measure of overall risk in the proposed research is taken as variance.

The following formula will be used for calculation of variance:

$$Var_i = \sigma_i^{\,2} = \sum_{i=1}^{n} \{(R_i - R_{avg})^2 / n-1\} \qquad \ldots\ldots\ldots\

10.4.2 To calculate the Systematic Risk of Sector Portfolio

According to Sharpe's Single Index model, return on any asset is related, to a certain extent, to the variations in the return on the Market Index of stock exchange. Therefore, the following equation for the return on an asset (Elton et al., 2007) can be written as:

$R_t = a + \beta R_M + \varepsilon_t$ .....(2)

Where

R_t = Return on security/portfolio

R_M = Return on market portfolio

a = Constant term

β= Measure of systematic risk ie Beta

ε_t = Residual error

The parameter β is supposed to be constant and it measures the responsiveness of the security's return towards a change in the return of market portfolio. The hypothesis for the disturbance term ε_t is that its expected value is zero and has a standard deviation of σ^2 (Bilbao et al. 2007)

The equation for the asymmetric betas estimation is:

$R_t = a + \beta^U D_t^U R_M + \beta^D D_t^D R_M + \varepsilon_t$ .....(3)

Where, R_t , R_M, a and ε_t are defined in equation (1), while β^U *and* β^D are the upside and downside betas respectively. Upside beta is the factor sensitivity of the sector index when the market rises. Downside beta is the factor sensitivity of the sector index when the market declines. Variables D_t^U *and* D_t^D are dummy variables which denote the upside and the downside market conditions respectively. Systematic Risk will be calculated as per the following formula:

$\sigma^2_{i\,sys} = \beta_i^2 \sigma^2_M$ ---------- *(For constant beta model)* .....(4)

$\sigma^2_{i\ u\ sys} = \beta^U{}_i^2 \sigma^2_{MU}$ ---------- *(For asymmetric beta model when the market is up)* .....(5)

$\sigma^2_{i\,D\,sys} = \beta^D{}_i^2 \sigma^2_{MD}$ ---------- *(For asymmetric beta model ,when the market declines)* .....(6)

Where:

$\sigma^2_{i\,sys}$ = Systematic risk of a security.

σ^2_M = Variance of the market portfolio

$\sigma^2_{i\ u\,sys}$ = Upside systematic risk.

$\sigma^2_{i\,D\,sys}$ = Downside systematic risk

σ^2_{MU} = Upside Market variance

σ^2_{MD} = Downside market variance

10.4.3 To calculate the Unsystematic risk:

$\sigma^2_{i\ unsys} = \sigma_i^{\ 2} - \beta_i^2 \sigma^2_M$ .....(7)

Where

$\sigma^2_{i\ unsys}$ = Unsystematic risk of the security

Unsystematic risk for the upside and downside market will be calculated separately using the same formula.

10.4.4 To test the phenomenon of volatility clustering and conditional volatility:

To exhibit whether the stock prices exhibit the volatility clustering, Autoregressive Conditional Heteroscedasticity ($ARCH_{11}$) originally developed by Engle will be applied. Conditional volatility estimates will be calculated using ARCH/GARCH Class of Models

10.4.5 To test the Accuracy of Forecasts:

For evaluating the forecasts obtained from the ARCH/GARCH class of models three models namely Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and Mean Absolute Percent Error (MAPE) have been used.

The models may be defined as follows:

$$RMSE = \sqrt{\frac{1}{T-(T_1-1)}\sum_{t=T_1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)^2} \quad \text{.....(8)}$$

Where $\hat{\sigma}_t^2$ is the one-step-ahead forecast volatility, σ^2_t is the actual volatility, and T is the total size (in-sample + out-of-sample), and $T_1$is the first out-of-sample forecast observation.

The MAE is defined as:

$$MAE = \frac{1}{T-(T_1-1)}\sum_{t=T_1}^{T} | \hat{\sigma}_t^2 - \sigma_t^2 | \quad \text{.....(9)}$$

The MAPE is defined as:

$$MAPE = \frac{100}{T-(T_1-1)}\sum_{t=T_1}^{T} | \frac{\hat{\sigma}_t^2 - \sigma_t^2}{\sigma_t^2} | \quad \text{.....(10)}$$

10.4.6 To test the severity of losses:

To test the maximum possible loss, daily Value at Risk (VaR) has been calculated using conditional volatility data obtained through AR(p)-GARCH(p,q) process. VaR estimates will be calculated at both 95% and 99% level of confidence. VaR will be calculated using the following formula:

$$VaR_{t+1}^{cl} = -\sigma^{GARCH}{}_{t+1}\Phi^{-1}(cl) \quad \text{.....(11)}$$

Where,

VaR_{t+1}^{cl} = one day ahead Value at Risk estimation.

$\sigma^{GARCH}{}_{t+1}$= One day ahead Conditional standard deviation obtained from AR(p)-GARCH (p,q) process.

$\Phi^{-1}(cl)$ = critical value that can be read off from the normal distribution table at given confidence level.

For example, if confidence level is chosen to be 95% with a corresponding critical value of 1.645, VaR value for the standardized return is 1.645 which means one can be 95% sure that the return will not be worse than minus 1.645 in the next day.

10.4.7 To explore the existing risk management tools:

Risk management tools are applied both at the macro level as well as the micro level.

The study intends to explore the existing risk management tools such as SEBI rules and regulation; diversification; arbitratge; hedging etc. in the Indian stock market.

11. PLAN OF WORK:

The work plan will be phased over a period of 30 months. The broad areas of work over this period will be as follows:

- 0 – 6 months – Study of existing literature on different models including GARCH / VaR, with special emphasis on sectoral indices and collection of data sets.
- 6 – 12 months – Application of existing models to data sets using software tools .
- 12 – 18 months – Analysis of results and comparison with the results reported by other authors on this topic; presentation of results in conferences.
- 18 – 24 months – Identification/ Design of a universal model and its testing; publication of research work in the form of research papers in journals.
- 24 – 30 months – Writing of thesis and publication of research papers.

12. PLAN OF THESIS:

The proposed plan of thesis will be as follows:

- Title of thesis
- Certificates
- Acknowledgement
- Abstract of thesis
- Chapter 1: Introduction
- Chapter 2: Review of literature
- Chapter 3: Models for estimation of VaR and prediction of volatility
- Chapter 4: Data sets: Sectoral Indices
- Chapter 5: Results and Discussion
- Chapter 6: Search for a Universal model or Designing and testing of an improvised (new) model
- Chapter 7: Conclusion and Future prospects

- References
- Appendix
- Bio data of the candidate
- Reprints & Preprints of Research papers

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